Innovation forecasting model

Technequality

Understanding the relation between technological innovations and social inequality

Innovation forecasting model

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Description of deliverable

Deliverable 1.3 reports on the adaptation to the baseline Cedefop Skills Forecast 2018 to better account for the impact of automation on jobs in Europe till 2030. Because the speed at which automation will penetrate industry sectors and affect occupations is uncertain, we use OECD data on the automation risk by occupation to develop a number of hypothetical, but realistic scenarios. The labour market outcomes of these scenarios will be reported in Deliverable 1.4, to be released end 2019.

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1. Introduction

Economic models predict that technological innovations such as robotics and artificial intelligence (AI) will have a profound impact on the economy and the labour market (Acemoglu & Restrepo, 2018). Estimates for the automation risk of occupations range from 47% (Frey & Osborne, 2017) to 9% (Arntz et al., 2016) and crucially depend on the task content of occupations, as routine tasks can easily be automated, but non-routine tasks are harder to automate (Autor, 2015). Despite the growing possibilities that AI offer to automate non-routine tasks, so called engineering bottlenecks are still expected to remain (see the discussion in Levels et al., 2019). One purpose of WP1 is to further develop our understanding and to create an evidence base of potential consequences of automation for European labour markets. The work carried out in this task combines the standard EU forecasting model for the labour market, and updated data of automation risks in the EU Member States.

In this paper, we document the main line of our approach to quantifying the impact of technologies on labour. The basis for this exercise is the Cedefop Skills Forecast model 2018 that offers quantitative projections of the future trends in employment by industry sector and occupational group using harmonized data and methodologies for all countries of Europe (Section 2). The novelty of our approach is twofold:

- We further develop the Cedefop Skills Forecast model to make it a unique tool for forecasting the impact of technologies on labour in a way that is comparable across countries of Europe.
- We develop a range of plausible scenarios of automation to account for the fact that the development, deployment, and adoption of new technologies is characterised by substantial uncertainties (Section 3). This allows us to be the first to assess the potential consequences of technologies for the labour market across realistic scenarios. A qualitative judgement of the relative likelihood of different scenarios can then be applied.

The details of the approach and the outcomes of this exercise will be published in December 2019. An uncertainty we will not be able to address with the model, is how new technologies affect the nature or task content of jobs (Levels et al., 2019). This is because it is rather hazardous and speculative to try to quantify the job creation potential of technologies (Section 4).

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2. Baseline forecasts

The baseline labour market forecast used is the Cedefop Skills Forecast 2018 (see Cedefop, 2018b, Cedefop, 2018c, Cedefop, Eurofound, 2018), hereafter Cedefop forecast. The Cedefop forecast chiefly relies on data published by Eurostat (Labour Force Survey) and provides data of the current structure, and future trends, of the EU labour market. The development of the Cedefop forecast employs seven modules to forecast demand and supply of labour disaggregated by sector, occupation, and qualification level (see Figure 1). Briefly, the main elements of the approach are:

1. demand side of the economy
2. supply side of the labour market: number and characteristics of the economically active, including skills and qualifications
3. imbalances, comparing demand and supply side modules, and reconciliation

The chosen time horizon for this analysis is 2030. Forecasting for further time horizons entails a higher risk of economic and policy uncertainties.

The baseline forecasts make no specific assumptions about how automation affects (future) employment demand. Automation, of course, affected past employment demand in the data we use as input through various mechanisms, and this is reflected in the baseline forecasts. Workplace technologies are typically designed to substitute workers for capital, leading to a decline in the demand for labour (substitution effect). However, there are several countervailing economic forces that can compensate for the initial labour-saving impact of the adoption of technologies. For example, automation can reduce the prices of goods and services, which can in turn increase the demand for products and labour. Moreover, technologies can be productivity enhancing, thereby increasing the demand for workers who perform tasks that complement such technologies.

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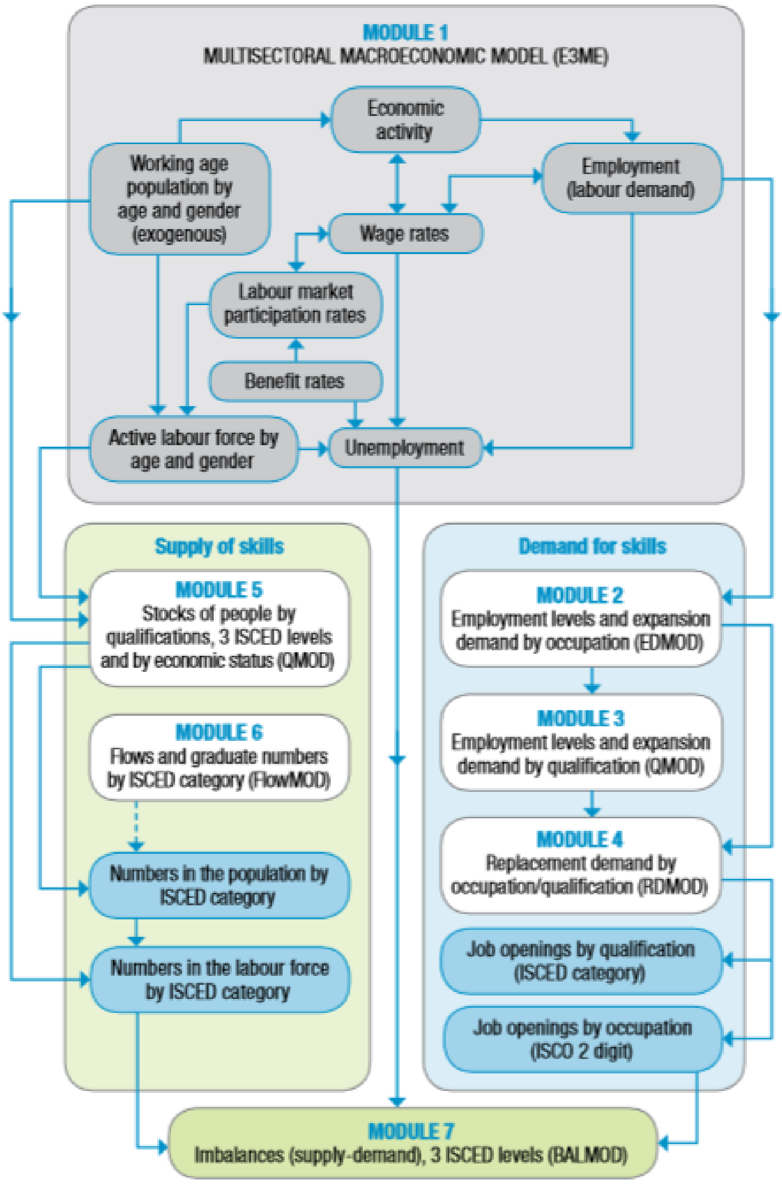
Figure 1. **Modelling skill supply and demand**



Source: Cedefop, Eurofound (2018, p.15).

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3. Scenario design

Automation risk

A body of literature has built upon Frey and Osbourne's (2017) seminal estimation of the automation risk of occupations. However, literature suggests the automation risk of occupations crucially depends on the task composition of these occupations (Autor, 2015). To account for this, our forecasting models use automation risk data estimated by the OECD (Nedelkoska & Quintini, 2018) that was provided to us for this H2020 project. The source data provides 2-digits ISCO occupation-level automation risk for 20 EU Member States. Specifically, the data provide the share of each workers in each occupation at risk of automation, by three categories: high (>70%), significant (50-70%), and low (<50%). For EU Member States not covered by the OECD data, we computed the EU average in the data for each occupation and imputed this when data was missing.

Technology potential

The basis of developing scenarios in this work is to select plausible ranges for modelling parameters, given the factors which affect the pace and extent of automation. From the conception of a given technology, there is a significant journey to its full economic exploitation. Once a general-purpose technology is 'discovered', commercial applications are developed. Commercial applications will only be exploited once it is profitable to do so. After initial application, technology takes substantial time to reach its full potential. There are three broad categories of factors to consider: technological, economic, and socio-political.

In terms of the mechanics of applying automation risk data to the Cedefop forecast, we distinguish between the 'technology potential' parameter and the 'deployment potential' parameter. The 'technology potential' parameter captures uncertainty in the estimation of automation risk. This parameter concerns only technological potential and is time invariant. The 'deployment potential' parameter controls the maximum realisation, each year, of the technological automation potential. This parameter captures developments of commercial solutions, economic feasibility, and aspects of the socio-political dimension. This parameter is relaxed over time.

A range of parameter values are used across scenarios to explore central and boundary scenarios:

1. The 'technology potential' parameter falls within the automation risk range as estimated by Nedelkoska and Quintini (2018). That is, for jobs that Nedelkoska and Quintini (2018) identify in the 'high risk' category, the chance of automation is greater than 70%. This means that the maximum realisation is in the range 70-

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100%. In the scenarios we use the lower bound, midpoint, and upper bound of the automation risk range: for the high risk category, this is 70%, 85%, and 100%respectively.

2. The 'deployment potential' parameter is set such that full technology-potential is realised by either 2035, 2055, or 2075 to reflect different speeds of technology adoption. The parameter is relaxed linearly from zero to one between 2020 and these years.

Policy scenarios

In the above-described scenarios we assume that the 'deployment potential' parameter evolves linearly within the forecasting period. However, the speed at which automation penetrates in EU countries, industry sectors and occupations will depend on at least two factors: Member States' employment protection legislation, and industry sectors' exposure to competition:

1. Employment protection legislation (EPL): in countries where employment protection legislation is tight, it is more difficult for firms to displace workers and replace them by machines. We normalize OECD's EPL indicator (https://www.oecd.org/employment/emp/oecdindicatorsofemploymentprotection.htm). We restrict annual automation to new job opportunities in countries in which there are relocation conditions for redundancy. This is to reflect the expected lower pace of deployment in countries with tight employment legislation.
2. Competition: in industry sectors where price competition is high, firms will have to adopt new technologies to remain competitive. This will speed up the adoption of automation in sectors. We use industry-specific competitiveness by constructing trade intensity indicators, using E3ME data. We multiply the 'deployment potential' parameter by this index to reflect the expected faster pace of deployment in sectors that are highly competitive.

4. Employment creation

Although technological innovations are penetrating all industry sectors and replace labour inputs (Oxford Economics, 2019), technology also generates employment and increases productivity (Graetz & Michaels, 2018) such that the net effect on employment is unclear. There is evidence that automation so far has not resulted in a net loss of jobs (Autor & Salomons, 2018). In this exercise we will not provide a quantitative estimation of the job creation potential of automation since this is rather speculative and macro-empirical evidence on the link between technology and employment – that also considers labour-enhancing mechanisms (e.g., indirect income and price compensation mechanisms) – is

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scarce (Vivarelli, 2014). Levels et al. (2019) discuss the job creation potential of technological innovations.

5. Conclusion

Technological innovations (robotics, artificial intelligence) are expected to profoundly impact the economy and the labour market, and one of the purposes of this H2020 project is to assess this impact. This paper documents the main line of our approach to quantifying the impact of technologies on labour. The novelty of our approach is that we build forth on existing Cedefop Skills Forecast model 2018 to 1) quantify the impact of technologies on labour in a way that is comparable across countries of Europe, and 2) develop a range of realistic scenarios to account for the fact that the development, deployment, and adoption of new technologies is characterised by substantial uncertainties. The labour market outcomes of these scenarios will be reported in Deliverable 1.4, to be released in December 2019.

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